

Tax Knowledge Diffusion via Strategic Alliances

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Abstract

This study examines strategic alliances as channels for tax knowledge diffusion between firms. Despite solid insights on within-firm determinants of tax planning, little is known about tax knowledge diffusion via cross-firm connections. Since theory suggests that the role of strategic alliances in tax knowledge diffusion is ambiguous, we test our notion empirically. To tease out potential tax knowledge diffusion, we analyze changes in the tax planning behavior of high-tax firms in strategic alliances with low-tax firms in comparison to high-tax firms in strategic alliances with other high-tax firms. We apply a multivariate regression model, a difference-in-differences approach and use basic textual analysis to identify the main business purpose of a strategic alliance. We find a substantial increase in the tax planning behavior of high-tax firms in strategic alliances with low-tax firms relative to high-tax firms in high-tax strategic alliances. Additionally, our results suggests that high-tax firms are able to adjust their tax planning behavior within two years of network initiation when cooperating with low-tax firms. Because we are also able to provide a series of robustness checks, we interpret the identified responses to be consistent with existing tax knowledge diffusion via strategic alliances.

Keywords: Corporate Tax Planning/Avoidance, Knowledge Diffusion, Network, Strategic Alliance.

JEL Qualification: C31, G34, H26.

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1. Introduction

Varying levels of control and commitment to affiliates allow a firm to tailor its operational organization to its actual needs. One means of striving for optimal corporate institutionalization is cooperation with other firms. The relevance of this investment alternative is emphasized by the observation that firms currently plan to disrupt other industries by entering them via partnerships and cooperation (PwC, 2018). Generally, cooperation is expected to lead to information gathering and knowledge spillovers (e.g., see Higgins and Rodriguez (2006)), which are intuitively desirable for both investing firms and outsiders, such as governmental institutions. However, recent literature suggests that cross-firm connections could play a crucial role in the diffusion of tax planning practices between firms. Consequently, the perception and valuation of such spillovers would highly depend on the respective point of view. To the best of our knowledge, very little is known about the interplay of cooperation and corporate taxation. Thus, the key innovation of our study lies in analyzing whether strategic alliances serve as channels for tax knowledge diffusion between firms.

Generally, corporate cooperation is arranged either as a separate legal entity with equity participations for the involved parties or on a contractual basis. While the former type is usually referred to as (equity) joint venture, the latter is a so-called strategic alliance. Differences between joint ventures and strategic alliances are, however, not limited to their contractual/equity basis. Basically, strategic alliances may be regarded as “lying somewhere in between single-firm activity and spot contracting” (Lindsey, 2008), involving mutual commitment not typically found in arm’s-length market transactions but having less impact on the partnering firms’ operations than equity joint ventures (Chan et al., 1997). In contrast to equity joint ventures, strategic alliances themselves are not subject to corporate taxation. This is useful for us, as we are not interested in whether firms potentially use joint ventures as vehicles in tax planning activities but in whether cooperation may serve as a channel through which tax knowledge diffuses between firms. We thereby define tax knowledge as a firm’s ability to maximize its nonconforming tax planning activities.

We empirically exploit information on strategic alliances, which we also refer to as “networks”, between publicly traded US firms. Given that accounting data are available for a network’s participants, we

reshape data from the alliance to the participant level (network-firm-observations). Our base sample contains 4,159 network-firm-observations, which translate to 2,064 strategic alliances by 1,603 unique firms and 19,447 overall firm-year-observations between 1994 and 2016. Among these observations, we identify low-tax and high-tax networks. These are characterized by the presence of at least one low-tax firm as a participant or by initiation by undersheltered firm respectively (high-tax firms). To tease out (potential) tax knowledge diffusion, we analyze changes in the tax planning behavior of high-tax firms in strategic alliances with low-tax firms in comparison to high-tax firms in strategic alliances with high-tax firms. Thereby, we rule out alternative explanations, such as the overall influence of a network on a firm's tax planning behavior or reversion to the mean. We gain insights into the actual business of a network by applying a basic textual analysis approach. For our inferences, we apply a multivariate regression design and a difference-in-differences (DiD) model, which both complement a descriptive analysis. Covariates on partner, network and firm characteristics are included in the regression models and account for a broad range of influences. We find a substantial increase in the tax planning behavior, measured as cash taxes paid, of high-tax firms in strategic alliances with low-tax firms relative to high-tax firms in high-tax strategic alliances. Consequently, the results from our analyses support strategic alliances as channels through which tax knowledge diffuses between firms. Additionally, we test whether partner characteristics intensify or mitigate the identified learning effects but find that tax knowledge diffusion via strategic alliances is rather unaffected by such heterogeneity.

Our study refers to the emerging literature on channels through which tax knowledge diffuses between firms. Despite solid insights on within-firm determinants of tax planning (Lisowsky, 2010), little is known about cross-firm connections in this field. By examining a potential determinant of cross-sectional variation in tax planning practices among firms, we follow the calls for contributions to the understanding of this matter (Cen et al., 2018; Dyreng and Maydew, 2017; Wilson, 2009). Recent research has turned to cross-firm connections, analyzing board ties (Brown, 2011; Brown and Drake, 2014), banks (Gallemore, Gipper, and Maydew, 2018), human capital turnover (Barrios and Gallemore, 2018), auditors (Frey, 2018; Lim et al., 2018) and the supply chain (Cen et al., 2017, 2018). We extend this literature by analyzing the role of strategic alliances in tax knowledge diffusion. Since strategic alliances are established on a peer-to-peer basis between the participants and are thus directly associated

with a firm's organizational level, we discuss whether networks provide a conceptual framework for successful tax knowledge diffusion. Subsequently, we test our notion empirically.

We further contribute to the management literature on knowledge diffusion via strategic alliances. Empirical inferences in such studies are usually based on the contracting parties' stock price performance (Boone and Ivanov, 2012; Mohanram and Nanda, 1996; Chen, King, and Wen, 2015; Anand and Khanna, 2000), return on equity, (cash flow) return on assets (Chan et al., 1997; Porrini, 2004) and post-reorganization performance (Cai and Sevilir, 2012; Higgins and Rodriguez, 2006; Ishii and Xuan, 2014; Porrini, 2004). While firms are often found to benefit from what they learn in alliances in other contexts, not all corporate practices diffuse in the same way (Cai et al., 2014). To the best of our knowledge, we are the first to measure knowledge diffusion via strategic alliances based on a firm's tax planning behavior. Our study therefore not only aligns with accounting and management research but also develops a new measure of knowledge diffusion via strategic alliances.

In the next section, we thoroughly review the related literature to discuss how tax knowledge diffuses between firms and which role strategic alliances could take in such diffusion. Subsequently, we explain our data exploitation and identification strategies. We discuss an appropriate research design and then present and discuss the results of our study. Before this paper closes with a brief conclusion, we provide several sensitivity analyses.

2. Conceptual Framework & Prior Literature

2.1. Channels for Tax Knowledge Diffusion

The extensive research that considers firm-level characteristics to explain the development and variation of tax planning activities by firms underlines the perceived importance of corporate taxes in economic theory, politics and society (for comprehensive reviews, see Hanlon and Heitzman (2010) and Wilde and Wilson (2018)). Despite these solid insights on the within-firm determinants of tax planning (Lisowsky, 2010), little is known about tax knowledge diffusion via cross-firm connections. Given the substantial economic impact of tax planning activities (Tørsløv, Wier, and Zucman, 2018), one intuitively aligns practices by tax advisors with increased tax planning. Recent research suggests the existence of further channels, by investigating tax planning ecosystems between firms. Consequently, a “better understanding of the actual tax strategies being used” is needed (Dyreng and Maydew, 2017). Brown (2011) pioneered in this literature strand by examining the spread of a specific tax planning tool, the corporate-owned life insurance shelter. While she finds that board interlocks and (to some extent) geographical proximity increase the probability that a firm adopts the shelter from a prior user, she does not find significant shelter adoption via shared audit firms. The latter result, although theoretically convincing due to independence regulations on audit services, is somewhat surprising given the large literature on auditors trespassing their limited scope of function (Aobdia, 2015; Cai et al., 2016; Dhaliwal et al., 2016; McGuire, Omer, and Wang, 2012). Calibrating from the audit-firm level to the individual audit engagement partner, Frey (2018) suggests that the engagement of a German tax certified auditor, who signals high competency in taxes, is associated with higher effective tax rates at client firms. In contrast, Lim et al. (2018), find that Chinese firms with stronger connections to low-tax firms through individual audit partners show lower effective tax rates. Further disentangling intermediaries as channels for tax knowledge diffusion, Barrios and Gallemore (2018) document that firms exhibit increasing tax planning when they hire tax staff from sophisticated tax planners. This finding is consistent with inferences from analyzing board ties to low-tax firms (Brown and Drake, 2014). Gallemore, Gipper, and Maydew (2018) show that firms experience meaningful tax reductions when they start a relationship with a bank whose existing clients engage in tax planning.

[Figure 1]

These studies are conceptually aligned by the presence of intermediaries who implement tax planning expertise in their set of contracts and transfer the tax knowledge gained to other parties they are contracting with. Intermediaries are found to play a key role in the acquisition and dissemination of information in many research fields (e.g., see Di Maggio et al. (2019)). In the context of tax knowledge diffusion, this could, for instance, be perceived as a violation of auditor independence (McGuire, Omer, and Wang, 2012). Figure 1 categorizes prior research on channels through which tax knowledge diffuses. It aligns the framework (institutional setting) to identified channels. While research on tax knowledge diffusion focuses on the role of intermediaries, Cen et al. (2017) and Cen et al. (2018) analyze peer-to-peer contracting between firms. Specifically, they focus on tax knowledge diffusion via the supply chain and document that customers and suppliers both increase tax planning activities once their relationship is considered dependent. Strikingly, Cen et al. (2018) suggest that customers and their suppliers share tax planning benefits through lower product prices. While evidence for intended sharing of tax benefits is scarce (for instance, see Erickson (1998) and Erickson and Wang (1999)), an explicit transfer of tax knowledge aligns the “supply chain channel” with research on intermediaries.

2.2. Strategic Alliances and Tax Knowledge Diffusion

With our study, we broaden the research on how tax knowledge diffuses between firms via peer-to-peer contracting. We therefore elaborate on different characteristics of tax knowledge, which could impede or facilitate spillovers in strategic alliances, and subsequently resolve whether strategic alliances establish an organizational form of collusion that allows for knowledge spillovers.

2.2.1. Tax Knowledge

Repeated business transactions are found to enable knowledge spillovers (Isaksson, Simeth, and Seifert, 2016). However, not all corporate practices diffuse in the same way (Cai et al., 2014), as major barriers to knowledge spillovers are shown to be knowledge-related factors (Szulanski, 1996). While explicit knowledge can easily be codified and is systematically transferable, tacit knowledge is hard to formulate and communicate because it “is deeply rooted in action, commitment, and involvement in a specific context” (Nonaka, 1994). Consequently, the more (tax) knowledge qualifies as explicit, the more easily transferable it should be (Meier, 2011). When classifying tax knowledge, one might reflexively refer to it as tacit given the substantial complexity of corporate taxes (Hoppe et al., 2019) and the increased uncertainty (Dyreg, Hanlon, and Maydew, 2018; Guenther, Matsunaga, and Williams, 2017) and costs of (Hundsdoerfer and Jacob, 2018) tax planning. One also has to consider that know-how is somewhat sticky, difficult to codify and therefore more tacit than pure information (Kale, Singh, and Perlmutter, 2000). However, anecdotal evidence suggests that tax shelters, such as the German family office shelter for limited partnerships, are repetitive among firms and not limited to a particular industry. Recent findings suggest tax knowledge to rather be of explicit nature, given the inferences on the corporate-owned life insurance shelter (Brown, 2011) or lease-in, lease-out transactions (Wilson, 2009). Lisowsky (2010) further argues that a significant portion of tax shelters serve as mass market tax saving ideas for advisors.

2.2.2. Successful (Tax) Knowledge Diffusion

According to Rogers (2003), diffusion requires communication through channels over time among members of a social system. In accomplishing a common goal, the contracting parties of a strategic

alliance are engaged in joint problem solving via a social system. Consistent with this, cooperation is found to mitigate problems ensuing from cultural differences (Kogut and Singh, 1988). Spillovers are also more likely to occur in cases of a high frequency of interactions between firms (Isaksson, Simeth, and Seifert, 2016) and with increasing partner trustworthiness (Jiang et al., 2016). Regarded as “lying somewhere in between single-firm activity and spot contracting” (Lindsey, 2008) and presenting increased mutual commitment in comparison to arm’s-length market transactions (Chan et al., 1997), strategic alliances further comply with the diffusion requirements proposed by Rogers. Empirical inferences about knowledge diffusion via strategic alliances are usually based on the contracting parties’ stock price performance (Boone and Ivanov, 2012; Mohanram and Nanda, 1996; Chen, King, and Wen, 2015; Anand and Khanna, 2000), return on equity, (cash flow) return on assets (Chan et al., 1997; Porrini, 2004) and post-reorganization performance (Cai and Sevilir, 2012; Higgins and Rodriguez, 2006; Ishii and Xuan, 2014; Porrini, 2004). Other scholars apply exploratory approaches by conducting surveys (Dyer and Hatch, 2006) or interviews (Inkpen, 2008). Often, firms are found to benefit from what they learn in alliances in other contexts (Porrini, 2004). Based on these findings, strategic alliances should provide a good channel for the successful diffusion of tax knowledge.

Although cooperation is found to be associated with knowledge spillovers, tension arises from various aspects. First, limits to the recipient’s absorptive capacity create a barrier to knowledge diffusion (Dyer and Hatch, 2006; Szulanski, 1996). With regard to tax planning, cooperation could also induce complexity in the contracting parties’ organization and reduce a firm’s ability to fine-tune the tax sheltering of its affiliates (Desai, Foley, and Hines, 2004). Additionally, both cooperation (Chen, King, and Wen, 2015) and tax planning are found to increase an organization’s uncertainty (Dyreng, Hanlon, and Maydew, 2018). Thus, even prudent managers could expect the marginal disutility of uncertainty to exceed the benefits of acquired tax knowledge. Furthermore, firms need to find ways not only to derive critical know-how from their alliance partners but also to protect themselves from losing their own core capabilities (Kale, Singh, and Perlmutter, 2000). Khanna, Gulati, and Nohria (1998) frame this in the context of earning private benefits in an alliance, which permits the firm to apply what it learns to its business outside the scope of the alliance and therefore harms the cooperation by inducing underinvestment in shared learning.

2.2.3. Mechanisms

Inkpen (2000) describes learning through networks as a multi-stage process, consisting of forming a network, gaining access to knowledge and adopting the knowledge. However, there is little evidence on how knowledge diffusion (i.e., spillover) occurs. Chan et al. (1997) identify optimal decision making authority, organizational flexibility and control of opportunistic behavior as major drivers for value creation within a strategic alliance. Khanna, Gulati, and Nohria (1998) argue that although contracting parties must invest in learning, both parties need not earn private benefits. They argue that a firm [with poor tax knowledge]¹ would not have an incentive to continue the alliance once it had earned private benefits [tax knowledge spillover] if its private benefits exceeded the common benefits. The other party [with sophisticated tax knowledge] would then “race” to earn benefits itself before termination of the alliance. As such racing behaviors appear to be mutually reinforcing, common benefits would still be attainable (Khanna, Gulati, and Nohria, 1998). Furthermore, strategic alliances enhance managerial flexibility because the contracting parties are not fully committed to the investment (Chen, King, and Wen, 2015), while Fiol and Lyles (1985) highlight that the probability of learning increases with an organizational structure that allows innovativeness and new insights. Employees who are seconded to a strategic alliance are involved in not only the alliance’s business as such but also the monitoring of the alliance and the partner. Within-organization reporting thus creates opportunities for experience-sharing. The observation of tax planning effectively implemented by other participants in a network could increase a firm’s management confidence in implementing the respective tax planning activity as well. This learning by observation would be consistent with knowledge diffusion being a gradual process of dissemination (Szulanski, 1996), with increasing probability of uniformity of actions over time in networks (Gale and Kariv, 2003) and with anecdotal evidence on tax advisors heavily pitching tax planning ideas across the population of firms with only partial success from the spot. Gained confidence could overcome the (irrational) fear of reputational costs from engaging in tax planning (Gallemore, Maydew, and Thornock, 2014; Hanlon and Slemrod, 2009). With regard to supply chains, Cen et al. (2018) suggest that intentional tax knowledge transfers enhance or at least maintain supply chain

¹ Content in square brackets is added by the authors.

stability. Strategic alliances are also exposed to instability that is inherent in their institutionalization and specific to cooperation. Cultural differences, product market competition, availability of new technology, cost differences, market entry barriers, deadlocks, or imitation of a partner cause this instability. Participants in a strategic alliance could therefore follow the intuition of Cen et al. (2018) and share tax knowledge to establish bonding mechanisms.

Given the aforementioned variety of potential mechanisms, we do not expect that tax knowledge diffusion via strategic alliances is exposing itself in (one) specific accounting measure(s). Rather more, the experiences of others and the communication structure between parties (analytically) explain information flows (Acemoglu et al., 2011; Blonski, 1999). Consequently, we expect tax knowledge diffusion via strategic alliances to be driven by several soft factors. If we observed actual exploitation of opportunities for tax knowledge diffusion, we could shed light on knowledge spillovers in peer-to-peer contracting. Thus, it remains an empirical question whether strategic alliances actually serve as channels for tax knowledge diffusion between firms.

3. Data

[Table 1]

3.1. Sample Construction

We exploit data on strategic alliances from Securities Data Company's (SDC) Platinum database on strategic alliances over the period 1994–2016.² SDC is widely used in relevant research on corporate cooperation (Anand and Khanna, 2000; Boone and Ivanov, 2012; Cai and Sevilir, 2012; Chen, King, and Wen, 2015; Ishii and Xuan, 2014), and its accuracy is generally perceived as very high for most items (Anand and Khanna, 2000). SDC issues data at the strategic alliance level. We reshape data from the alliance to the participant level because accounting data are available for the (publicly traded) contracting parties. For instance, a strategic alliance between two participants translates to a network-firm-observation for each of the two firms. Compustat provides us with firm-year-level accounting information, and we merge SDC and Compustat data using a firm's six-digit CUSIP number (at the level of the ultimate parent of the participant) as an identifier. Although SDC provides reliable network-observations from the beginning of 1990 onwards, we start our sample in 1994 due to changes in reporting requirements on cash taxes paid (Cen et al., 2017). We end our sample in 2016 to exclude any inferences from the 2017 US tax reform. Furthermore, we respectively consider strategic alliances between publicly traded firms incorporated and headquartered in the US and in which all contracting parties are identified in Compustat (Table 1 Panel A). Our base sample contains 4,159 network-firm-observations, which translate to 2,064 strategic alliances by 1,603 unique firms and 19,447 overall firm-year-observations.

² A list of the requested data items is available from the authors upon request.

3.2. Identification Strategy

[Figure 2]

3.2.1. Measuring Tax Knowledge

For purposes of this study, we define tax knowledge as a firm's ability to maximize its nonconforming tax planning activities. The lingua franca in measuring the degree to which a firm is able to succeed in this attempt is the effective tax rate, which puts tax expenses and pre-tax book income into perspective. The interpretation of effective tax rates is fairly straightforward, and an advantage is that, even though conceptually incorrect, they are widely used as input for corporate decisions on new investment (Graham et al., 2017). We base our inferences on the cash effective tax rate (*cash ETR*) because *cash ETR* also captures tax deferral strategies (Hanlon and Heitzman, 2010). Furthermore, we apply a multi-period (3-year) form of *cash ETR* (Brown and Drake, 2014; Barrios and Gallemore, 2018; Gallemore, Gipper, and Maydew, 2018), because we expect tax knowledge spillovers to occur more likely over time.

$$cash\ ETR3_{i,t=1} = \frac{\sum_{t=1}^3 (txpd_{i,t})}{\sum_{t=1}^3 (pi_{i,t} - spi_{i,t})} \quad (1)$$

The terms *txpd*, *pi* and *spi* correspond to their Compustat data item equivalents of cash taxes paid, pretax income and special items. Missing *spi* are reset to 0, while any *cash ETR3* with a negative denominator is reset to missing. Non-missing *cash ETR3* are winsorized at 0 and 1. By nature of this approach, *cash ETR3* would always be missing for the final (penultimate) firm-year of a firm in our panel. For the final (penultimate) firm-year, we therefore substitute *cash ETR3* with *cash ETR(2)*. Applying a forward-looking *cash ETR3* comes with the advantage that potential tax knowledge spillovers from strategic alliances can be directly linked to the year of network initiation.

3.2.2. Low-tax and High-tax Networks

For tax knowledge spillovers to occur, at least one network participant must possess sophisticated tax knowledge. Therefore, we classify the strategic alliances in our dataset into low-tax and high-tax networks. Applying a forward-looking *cash ETR3* for our output analysis has the advantage of aligning any influence on the *cash ETR3* directly to the year of network initiation. However, identifying low-

tax networks based on a forward-looking measurement would come with the disadvantage of concluding the type of input based on the output. For the identification of low-tax networks, we therefore consider a form of the *cash ETR3*, which is constructed over a three-year preceding period:

$$pre\ cash\ ETR3_{i,t=0} = \frac{\sum_{t=-2}^0 (txpd_{i,t})}{\sum_{t=-2}^0 (pi_{i,t} - spi_{i,t})} \quad (2)$$

For every $t = 1$ in which a new network is initiated, we consider the participants' initial *pre cash ETR3*, which is constructed from $t = -2$ to $t = 0$. For the first (second) firm-year of a firm in our panel, we substitute *pre cash ETR3* with *pre cash ETR(2)*. To increase the accuracy of our analysis, we require to observe the *cash ETR3* and *pre cash ETR3* of all participants in a network to be considered in our analysis (Table 1 Panel B). Figure 2 provides additional information regarding how we classify firms and networks as low-tax and high-tax observations. We identify low-tax firms based on their industry-adjusted *pre cash ETR3* and allocate firm-year observations into 4 bins (*pre taxrank*) according to the quartiles of the distribution of industry-adjusted *cash ETR3*. Based on this, any firm observation that is aligned with the first *pre taxrank* is treated as a low-tax firm in a network. A strategic alliance in which at least one participant qualifies as a low-tax firm is consequently treated as a low-tax network. Firms that do not qualify as low-tax firms are treated as high-tax firms, and networks in which none of the participants is a low-tax firm are qualified as high-tax networks. Thus, our identification strategy generally follows the classification method applied by Brown and Drake (2014), who focus on board ties with tax-avoiding firms. Because we are interested in whether strategic alliances serve as channels for tax knowledge diffusion between firms, we focus on high-tax firms in our analyses. We thereby distinguish between high-tax firms that invest in low-tax networks and high-tax firms that invest in high-tax networks (Table 1 Panel C). Further excluding multiple network initiations of one firm in a single year (to rule out overweighing of a firm in the panel), our identification strategy leads us to 197 observations of networks of high-tax firms to low-tax firms and 540 observations of networks solely among high-tax firms.

3.3. Information on Networks and Firms

[Table 2]

Panel A of Table 2 contains information on the distribution of *pre cash ETR3* by *pre taxrank*, which is used to identify low-tax networks. While the mean *pre cash ETR3* in the first bin of *pre taxrank* equals 7.08%, the average rises to 63.91% in the top *pre taxrank*. Generally, the overlapping distribution of *pre cash ETR3* by *pre taxrank* points towards industry specifics in the tax burdens of the firms in our sample. The overall mean of 30.66% for *pre cash ETR3* is relatively close to but below the federal corporate income tax rate of 35%, which is consistent with prior research on multi-period cash effective tax rates (e.g., Dyreng, Hanlon, and Maydew (2008)). Furthermore, Panel B of Table 2 contains descriptive statistics for firm-level characteristics, separated by the classification of firms as low-tax or high-tax and by network type for high-tax firms. Panel B also includes firm-level accounting information (*firm controls*), which are included in our regression analyses. Following Dyreng, Hanlon, and Maydew (2010), we show information on *EBITDA3*, *RnDExp3*, *AdExp3*, *SGA3*, *CapEx3*, *ChangeSale3*, *Leverage3*, *Cash3*, *MNE3*, *NOL3*, *Intangibles3*, *PPE3*, and *Size3*.³ Consistently with *cash ETR3*, these measures are constructed over rolling three-year periods. In Panel C of Table 2, we present information regarding the industry affiliation of networks and firms. Industry affiliation is determined on a two-digit SIC-code basis. It can be observed that the majority of networks operate in business services, while the investing firms are predominantly manufacturers and business service providers. For a better understanding of the networks in our sample, the Online Appendix provides additional information about a random selection of networks, including the date of network initiation, the investing firms, the qualification as high-tax or low-tax network and a brief deal description, which is extracted from SDC.

³ All variables are defined in detail in the Appendix.

4. Methodology

4.1. Regression Analysis

If engaging in low-tax strategic alliances is associated with tax knowledge diffusion, one should be able to identify increasing levels of tax planning at high-tax firms. Nevertheless, one could not draw any inferences if the influence of a network on a firm's tax planning behavior as such were omitted. Consequently, our main variable of interest *hightolow* is constructed as an indicator variable to distinguish between high-tax firms that enter into high-tax networks (*hightolow* = 0) and high-tax firms that engage in low-tax networks (*hightolow* = 1). By running our regression among high-tax firms, *hightolow* isolates the incremental effect a low-tax network exerts on the high-tax firm's *Tax Knowledge*:

$$\begin{aligned} Tax\ Knowledge_{i,t=1} &= \beta_0 + \beta_1 hightolow_{i,t=1} + \sum_n \beta_n partner\ controls_{i,t=1}^n \\ &+ \sum_l \beta_l network\ controls_{i,t=1}^l + \sum_k \beta_k firm\ controls_{i,t=1}^k \\ &+ \delta_{ind} + \tau_t + \varepsilon_{i,t}. \end{aligned} \tag{3}$$

By using indicator notation (*hightolow*), the coefficient estimate describes the effect from moving from one condition to the other. As we use a three-year rolling specification of a firm's cash effective tax rate (*pre cash ETR3*) for identification purposes, we primarily measure *Tax Knowledge* by *cash ETR3*. Consistently, Kim et al. (2019) suggest that firms are able to adjust their tax planning behavior within three years. Consequently, the coefficient estimate for *hightolow* would load negatively, if strategic alliances served as channels for tax knowledge diffusion. To alleviate concerns about interpreting a level-based dependent variable, we also construct the change-indicating variable *delta cash ETR3*, which is *cash ETR3* [$t_1; t_3$] scaled by *pre cash ETR3* [$t_{-2}; t_0$]. Given a suggested average life span for strategic alliances of five years (Chan et al., 1997), we also measure *Tax Knowledge* as *cash ETR5* and *delta cash ETR5*.

[Figure 3]

Because strategic alliances go beyond bringing together high-tax and low-tax firms, we include vectors of variables on *partner & network controls* in our main regression model. From Compustat data, we can infer whether network participants share an audit firm in the year of network initiation (*SameAuditor*). Furthermore, we hand collect the geographical distance (as the crow flies) between the zip codes of the network participants' headquarters to control for the potential impact of geographical proximity in tax knowledge diffusion (*Proximity*). We normalize *Proximity* between 1 for the closest and 0 for the farthest distance, which allows us to interpret the sign of the coefficient in agreement with the sign of a potential indicator variable for a geographical linkage (as, for instance, in Brown (2011)). In our main regression, we do not include an indicator for firms belonging to the same industry (*SameInd*), as we include industry fixed effects (δ_{ind}). Generally, business activities in a strategic alliance are in no way limited and could thus exert influence on the options of tax planning that are available for a network participant. Therefore, we are interested in the main business purpose of a strategic alliance (*network controls*). To derive this, we apply basic textual analysis. For illustration purposes, the word cloud depicted in Figure 3 shows the 50 most common words used in SDC's deal descriptions of *hightolow* networks. By systematically searching through the deal descriptions, we identify *PurposeWholesale*, *PurposeRnD*, *PurposeLicensing*, *PurposeService*, *PurposeMarketing*, *PurposeSupply*, and *PurposeManufacturing* as network activities, create respective indicator variables at the individual network level, and include these *network controls* in equation (3).⁴ Furthermore, we control for within-firm determinants of tax planning by including a vector of *firm controls*. Thereby, we follow Dyreng, Hanlon, and Maydew (2010) and include *EBITDA3*, *RnDExp3*, *AdExp3*, *SGA3*, *CapEx3*, *ChangeSale3*, *Leverage3*, *Cash3*, *MNE3*, *NOL3*, *Intangibles3*, *PPE3*, and *Size3*. Consistent with *cash ETR3*, these measures are constructed over rolling three-year periods. The Appendix includes a complete list of variable definitions. In addition to industry fixed effects (δ_{ind}), we include year fixed effects (τ_t) and cluster standard errors at the firm level (Petersen, 2009).⁵

⁴ The maximum correlation between *hightolow* and one of the *network controls* is with *PurposeWholesale* (=0.0930, not tabulated).

⁵ The sign and overall significance of our main variable of interest are not sensitive to design choices regarding fixed effects or clustering of standard errors.

4.2. Matched Panel: Difference-in-Differences

The regression model in equation (3) allows us to directly align tax knowledge diffusion, which should occur over time, with the year of network initiation. This approach allows us to easily account for *partner & network controls*, although it condenses our panel to a cross section. An alternative approach for identifying tax knowledge diffusion is to maintain the panel structure of our data and apply a DiD methodology. In this model, treatment is generally in alignment with *hightolow*. Additionally, we create an embargo period of eight years around a *hightolow*-observation, during which a firm may not enter into an additional network. The embargo period contains the three years preceding and five years subsequent to network initiation. Our sample allows firms to enter into a network at any point in time of their discretion. We therefore compose a matched panel by matching control observations (*hightolow* = 0) to treatment observations (*hightolow* = 1) based on year and industry affiliation. As we no longer exploit cross-sectional but panel data, we adjust dependent and control variables from multi-period measures to their single-year versions:

$$\begin{aligned} cash\ ETR_{i,t} = & \beta_0 + \beta_1 treated_i + \beta_2 post_t + \beta_3 treated * post_{i,t} \\ & + \sum_k \beta_k firm\ controls_{i,t}^k + \delta_{ind} + \varepsilon_{i,t}. \end{aligned} \quad (4)$$

In this model, *treated* measures the baseline difference in *cash ETR* that is not due to the presence of the treatment. The parameter *post* captures changes in *cash ETR* from before to after treatment. The parameter of interest is the interaction *treated * post*. It measures the effect on *cash ETR* that is due to the treatment (i.e., low-tax network of high-tax firm). We include industry fixed effects and the annual measures of *firm controls* as defined in the Appendix. Again, we base our inferences on standard errors clustered at the firm level (Petersen, 2009).

4.3. Descriptive Analysis

A firm's decision to engage in a network is intentional and not random, which could lead to biased sample selection. Nevertheless, it is important to note that our study does not compare network firms with non-network firms but instead focuses on a within-comparison of network firms. Nevertheless, once a firm experiences a knowledge spillover via a low-tax network, engaging in subsequent networks

could, to some extent, also depend on an expected learning effect. Our sample could thus be nonrandomly selected, leading to concerns about endogenous treatment assignment (with regard to scholars on strategic alliances, see Carpenter, Li, and Jiang (2012)). One may account for this empirically by constructing a two-stage estimator (Heckman, 1979). Identifying valid covariates, which predict treatment assignment while having no direct impact on the dependent variable, is, however, difficult (Bodnaruk, Massa, and Simonov, 2013; Chan et al., 1997; McGuire, Omer, and Wang, 2012). Following the recommendation by Lennox, Francis, and Wang (2012), we therefore want to highlight that our study potentially has an endogeneity problem that could affect inferences from OLS regressions. However, if tax planning were an endogenous choice based on having high effective tax rates prior to engaging in tax planning (Dyreng, Hanlon, and Maydew, 2008), tax planning research would generally face endogeneity concerns. Additionally, prior research indicates that firms consider expected high taxation, measured as country-level corporate income tax rate, in the host country of a strategic alliance to be acceptable (i.e., positively associated) when forming an international network (Owen and Yawson, 2013). For further mitigation purposes, we conduct a thorough descriptive analysis. As in our regression analyses, we analyze changes in the tax planning behavior of high-tax firms in strategic alliances with low-tax firms in comparison to high-tax firms in strategic alliances with high-tax firms. We start our descriptive analysis by comparing *pre cash ETR3* [$t_{-2}; t_0$] between the two groups. We then focus on our primary measure for *Tax Knowledge* in the year of network initiation, *cash ETR3* [$t_1; t_3$], and test the significance of differences between the groups and within-group change. We then analyze the difference in the within-group change by applying a z test following Paternoster et al. (1998):

$$z = \frac{b_1 - b_2}{\sqrt{SEb_1^2 + SEb_2^2}} \quad (5)$$

We also focus on an analysis of the development of *Tax Knowledge* for intensified networking by firms in our sample. We thereby test for the existence of a gradual learning effect.

5. Results & Discussion

5.1. Descriptive Insights

[Table 3]

The results of our descriptive analysis are depicted in Table 3. In Panel A, we compare changes in *Tax Knowledge* between and within groups. Interestingly, the mean of *pre cash ETR3* is very similar for high-tax firms in the period before investing in low-tax or high-tax networks, with 38.96% and 39.35%, respectively (p-value of difference 0.8613). This alleviates concerns about analyzing level measures of *Tax Knowledge* in equation (3). It also indicates that low-tax firms do not tend to stay among themselves by engaging in strategic alliances with sophisticated tax planners. For periods subsequent to the initiation of a network by high-tax firms, the distribution of *cash ETR3* points towards a completely different direction. While observations of *hightolow* = 1 are accompanied with a mean *cash ETR3* of 27.55%, networks solely among high-tax firms (*hightolow* = 0) are aligned to an average *cash ETR3* of 32.82%. The respective difference of 5.27% is also highly significant (p-value 0.0065). Generally, we observe substantial reductions in cash effective tax rates for both groups (within-group change), each being highly significant (p-values < 0.0000). These decreases could comprise reversion to the mean. However, this would not explain differences in the development between the groups. We therefore test whether the difference in the within-group change of 4.88 percentage points is significant and find it to be so (z-statistic -1.6994). In Panel B, we compare the development of *cash ETR3* for high-tax firms' involvement in low-tax and high-tax networks with a growing number of networks. In this test, we again observe lower levels of *cash ETR3* for high-tax firms in low-tax networks, with differences increasing in intensified networking. Although our descriptive analysis does not allow us to include further covariates, we interpret our findings to be consistent with the notion of strategic alliances serving as channels for tax knowledge diffusion. Therefore, we are interested in whether multivariate regression results further support this notion.

5.2. Regression Results

[Table 4]

5.2.1. Multivariate Regression

The main variable of interest in our regression analysis is *hightolow* because it isolates the incremental effect a low-tax network exerts on a high-tax firm's *Tax Knowledge*. In Panel A of Table 4, we show multi-period specifications of *Tax Knowledge* for equation (3) with *cash ETR3*, *delta cash ETR3*, *cash ETR5* and *delta cash ETR5*. By observing multi-period measures, we can link our inferences to the period of network initiation. For brevity, we report only the coefficient estimates for *hightolow* and *partner controls*. Throughout all specifications, the estimate for *hightolow* is negative and highly significant. In the specification with *cash ETR3* as the dependent variable, the estimate for *hightolow* has a magnitude of -0.0480 (p-value 0.0103), which is consistent with our descriptive inferences in terms of direction and magnitude. Because an overall network effect is absorbed by including high-tax firms in our regression and because the covariates on *partner, network & firm controls* account for a broad range of alternative explanations, we find it plausible to associate the (relative) increase in tax planning practices for high-tax firms in low-tax networks to be induced by the presence of the low-tax firm in the network. Extending equation (3) to a change-indicating variable, *delta cash ETR3*, yields the same implications (p-value 0.0061). Furthermore, we extend our model to *cash ETR5* and *delta cash ETR5*, which are constructed identically to *cash ETR3* and *delta cash ETR3* but over five years subsequent to and including the year of network initiation as the dependent variables. The results for these specifications imply a slightly smaller magnitude (coefficient estimate for *(delta) cash ETR5* is -0.0376 (-0.1229)) in effects but are both negative and highly significant. Interestingly, the estimates for our *partner controls*, namely, *Proximity* and *SameAuditor*, do not surpass the usual levels of significance. In several additional analyses (see Section 6), we focus on the interactions of *hightolow* and *partner controls* to align our findings with prior research. Overall, our findings in Panel A convey that decreases in cash taxes paid are driven by the partner firm's tax planning behavior.

5.2.2. Difference-in-Differences

[Figure 4]

Panel B of Table 4 shows the results for our DiD analysis from equation (4). Any DiD specification relies on the parallel trend assumption. Otherwise, one could not empirically identify the posttreatment outcome absent the treatment. Usually, the parallel trend assumption is graphically examined by observing pretreatment trends of the dependent variable among the treatment and control groups. Accordingly, Panel A of Figure 4 provides visual evidence that the trends of *cash ETR* are parallel for treatment and control firms prior to the treatment (*hightolow* = 1). Consistent with our analysis on the full sample, it can also be observed that the pretreatment levels of *cash ETR* are very similar for the treated and untreated firms in the matched panel. While a direct empirical test for the parallel trend assumption is not possible, Patel and Seegert (2015) developed an approach to alleviate concerns about potential confounding factors. They suggest regressing the treatment indicator, time fixed effects and the interaction of the treatment indicator and time fixed effects on the dependent variable:

$$cash\ ETR_{i,t} = \alpha + treated_i + \tau_t + \tau_t * treated_i + \varepsilon_{i,t}. \quad (6)$$

They argue that failure to reject that the coefficient estimates for the interaction terms for $\tau_t * treated_i$ are jointly zero in the pretreatment period supports the parallel trend assumption. In Panel B of Figure 4, we therefore present the coefficient and the 95% confidence interval of the interaction of the treatment indicator and time fixed effects from equation (6) for the pretreatment years. First, none of the individual coefficients are significantly different from zero. More importantly, however, the p-value of the common trend test (the coefficients on $\tau_t * treated_i$ are jointly zero during pretreatment) is far beyond the usual levels of significance ($p = 0.7427$). Consequently, we are able to provide visual and statistical evidence for the parallel trend assumption.

In Panel B of Table 4, we depict several specifications of equation (4) with varying levels of *firm controls* and industry fixed effects (δ_{ind}). The estimate for the interaction of *treated* * *post* is negative and significant throughout all these specifications. Consequently, we find a negative *cash ETR* response to low-tax networks in comparison to high-tax networks for high-tax firms. Taken together,

the results from our descriptive and regression analyses are consistent with strategic alliances serving as channels through which tax knowledge diffuses between firms.

5.2.3. Adjustment Speed

We are further interested in how fast high-tax firms are able to adjust their tax planning behavior when cooperating with low-tax firms. Therefore, we estimate five specifications of equation (4). We extend the posttreatment period by one year with each specification. Thus, we notate $post = 1$ only for the year of network initiation $[t_1]$ first, and finish with $post$ equaling one for the complete embargo period $[t_1; t_5]$. The coefficient estimates for $treatment * post$ thus present the cumulative adjustment of a high-tax firm's tax planning behavior with progressing time (t_1 to t_5) when cooperating with low-tax firms (i.e. adjustment speed). The results for this analysis are presented in Panel C of Table 4. In concordance with theory suggesting that (tax) knowledge spillovers are likely to occur over time, the coefficient estimate for $treatment * post$ is not significant when the posttreatment period is limited to the year of network initiation. The coefficient estimate for the interaction, however, turns significant when $post$ equals one for t_1 and t_2 . Furthermore, the estimated effect continues to be significant when extending the posttreatment period to t_3 , t_4 and t_5 . Consequently, we assess high-tax firms on average to be able to adjust their tax planning behavior within two years of network initiation. These findings are consistent with recent research by Kim et al. (2019), who suggest that firms generally should be able to adjust their tax planning behavior within three years and that high-tax firms may increase their tax planning behavior even faster. Additionally, our results suggest that a firm's adjustment of its tax planning behavior, once implemented, stays constant over subsequent years.

6. Additional Analyses

[Table 5]

Thus far, we have considered the overall implications of low-tax networks for high-tax firms. We are also interested in the characteristics of network participants, which could intensify or mitigate the identified learning effects. First, prior research provides mixed evidence regarding the role of auditors in tax knowledge diffusion (Klassen, Lisowsky, and Mescall, 2016; Lim et al., 2018; McGuire, Omer, and Wang, 2012). Furthermore, Brown (2011) and Brown and Drake (2014) hypothesized that geographical proximity and identical industry affiliation of the participants could enhance knowledge diffusion.

In Panel A of Table 5, we compare two subsamples of networks, following the identification strategy of Brown (2011). One group consists of firms with their headquarters located in the same region, as defined by the Bureau of Economic Analysis (*SameBEARegion* = 1).⁶ The other group consists of firms with headquarters located in different BEA regions in the year of network initiation (*SameBEARegion* = 0). The intuition behind this approach is that shared membership in a geographical region should allow higher levels of interfirm interaction. We run specifications of equation (3) with (*delta*) *cash ETR*₃ as the dependent variable and are interested in the interaction terms of *hightolow* * *SameBEARegion* because these coefficient estimates comprise the incremental influence of geographical proximity on tax knowledge diffusion via low-tax networks. However, we observe a significant coefficient estimate of the main effect of *hightolow*. Neither *SameBEARegion* nor the interaction of the two are significantly different from zero. While this finding is generally consistent with the inferences by Brown (2011) on regional linkages, Cen et al. (2018) report that the correlation of effective tax rates is stronger for members of a supply chain that are located within the same geographical region.

In their hypothesis development, Brown and Drake (2014) argue that similar background knowledge and similar capabilities should have a positive impact on tax knowledge diffusion. They suggest that firms with the same industry affiliation share the same operating environment, which they expect to

⁶ The respective BEA regions are Far West, Great Lakes, Mideast, New England, Plains, Rocky Mountains, Southeast and Southwest.

enhance the effect. However, the results from comparing intra- and interindustry board ties fall short of their expectation. To test the potential effect of shared industry affiliation, we construct, coinciding with our approach in Panel A, two subsamples. One group consists of network participants who share industry affiliation (*SameInd* = 1), and the other group consists of firms with different industry affiliations (*SameInd* = 0). Consistent with Brown and Drake (2014) and in line with our inferences from geographical proximity, we cannot reject that the interactions of *hightolow* and *SameInd* are significantly different from zero. Although this finding seems somewhat counterintuitive, we want to highlight that tax shelters are often repetitive among firms, not limited by industry barriers and serve as mass market tax saving ideas (Lisowsky, 2010). However, we observe that the main effect of *SameInd* is negative and significant (p-value 0.0530 (0.0735) in the (*delta*) *cash ETR3* specification).

Finally, we extend our analysis of network heterogeneity to examine the role of shared audit firms. Therefore, we analyze whether firms share an audit firm in the year of network initiation. Based on this, we construct an indicator variable (*SameAuditor*) and interact it with *hightolow*. In specifications of equation (3) with *cash ETR3* and *delta cash ETR3* as dependent variables, the interaction terms for *hightolow * SameAuditor* respectively approach common levels of statistical significance. Our inferences take their place alongside a range of mixed inferences concerning auditors' impact on tax knowledge diffusion. While Brown (2011) does not find significant tax shelter adoption via shared audit firms, and Klassen, Lisowsky, and Mescall (2016) show that less tax aggressiveness in the past is associated with the auditor preparing a firm's tax return, Lim et al. (2018), and Cen et al. (2018) suggest that common auditors facilitate tax planning diffusion.

Overall, the results presented in Table 5 might easily be subject to misinterpretation. We do not posit that industry affiliation, auditor ties or geographical proximity do not have an incremental effect on how tax knowledge diffuses between firms. We are interested solely in whether partner heterogeneity accelerates or alleviates tax knowledge diffusion for high-tax firms that invest in low-tax networks. It appears that tax knowledge diffusion via strategic alliances is rather unaffected by such heterogeneity.

7. Robustness Checks

In this section, we examine the robustness of our primary findings with regard to alternative explanations and potential concerns about our identification strategy. Thereby, we rule out the possibility that our findings are unrelated to tax knowledge diffusion.

7.1. Alternative Explanations

[Table 6]

Applying three-year rolling measures of cash effective tax rates would systematically exclude from our sample network-firm-observations that occur at the first, second, penultimate and final firm-years of a network participant. For identification purposes, we substitute *[pre] cash ETR3* with *[pre] cash ETR(2)*. However, it is possible that strategic alliances serve as preliminary ties between successive acquirers and targets (Ishii and Xuan, 2014; Porrini, 2004). Survivorship bias could thus exert influence on our inferences. Consequently, we present a specification of equation (3) in Panel A of Table 6 in which we exclude nonsurvivors (i.e., firms with a network-firm-observations within the last two years of their presence in our panel) from the analysis. In this model, we still find the loading of *hightolow* to be significant (p-value 0.0571) and the economic magnitude to be consistent with our primary findings. This result indicates that our inferences are robust to survivorship bias.

Another alternative explanation of our findings could be that the difference in the levels of *Tax Knowledge* between the two groups in our sample is not induced by tax knowledge diffusion from low-tax firms to high-tax firms but by increases in *cash ETR3* for high-tax firms in high-tax networks.

[Figure 5]

Figure 5 depicts a kernel density plot of the distribution of *delta cash ETR3* for all high-tax firms. The dotted line at $x = 1$ indicates the threshold between a decrease and an increase for *cash ETR3* relative to *pre cash ETR3*. It can be observed that part of the high-tax firm population experiences increases in *cash ETR3*, which would, to some extent, not be consistent with knowledge diffusion. In Panel B of Table 6, we provide a specification of equation (3) in which we control for increases in *cash ETR3* by

including only observations of *delta cash ETR3* that are equal to or below the threshold of one. Again, our results indicate a negative and significant coefficient estimate for *hightolow*. Consequently, we are confident that our inferences are based on tax knowledge diffusion via low-tax networks rather than on increases in *cash ETR3* in the control group.

While we find high-tax firms to receive tax knowledge via low-tax networks, we have not considered the tax position of low-tax firms. Correspondingly to high-tax firms, low-tax firms can be bound to either high-tax firms or low-tax firms. Intuitively, there is little reason to expect incremental or even “negative” tax knowledge spillovers for low-tax firms bound to high-tax firms. To empirically control for this notion, we construct *lowtohigh*, which is an indicator that equals one for low-tax firms in networks with high-tax firms and zero for low-tax firms in low-tax networks. The results for this specification of equation (3) are presented in Panel C of Table 6. The coefficient estimate for *lowtohigh* is far beyond common levels of significance, with a p-value of 0.9961. This finding further supports our inferences of tax knowledge diffusion occurring among high-tax firms.

Since effective tax rates are influenced by tax payments and profitability, changes in *cash ETR3* could be solely income induced. This would to some extent speak against identifying tax knowledge diffusion. To account for this concern, we construct *ChangeEBITDA3*, which is the annual average growth rate in *EBITDA* from t_1 to t_3 (geometric mean). We then run equation (3) with *ChangeEBITDA3* as the dependent variable and find the coefficient estimate for *hightolow* to be nonsignificant (p-value 0.6569) and of small economic magnitude (Panel D of Table 6). From this, it follows that the identified effects are not linked to profitability.

[Figure 6]

Finally, our inferences could be explained by aspects of firm structure. Strategic alliances could, for instance, be formed around the same time a firm returns to profitability. Additionally, networks could open foreign markets for the participants, which would allow profit shifting to tax havens. However, there is little reason to expect high-tax firms to experience these changes in low-tax networks (*hightolow* contains the incremental effect on a firm’s tax position). Nevertheless, we depict the (three-year) annual average growth rates for foreign income (*ChangePIFO3*) and tax loss carry forward

(*ChangeNOL3*) separated by *hightolow* in Figure 6. It can be observed that the distributions are nearly identical. We interpret this as follows. Low-tax networks are channels for tax knowledge diffusion from low-tax firms to high-tax firms. They are, however, not necessarily accompanied by incremental structural changes for the group of “treated” firms. This complicates the identification of mechanisms through which tax knowledge diffuses, as this process seems to be driven by soft factors rather than by exposing itself in (one) explicit accounting measure(s) of firm structure.

7.2. Alternative Identification Strategy

[Table 7]

There are some judgment calls involved in classifying strategic alliances as high-tax- and low-tax networks and including an indicator variable in the respective regression. Therefore, we provide a modified model in which we regress the industry-adjusted *pre cash ETR3* [$t_{-2}; t_0$] of a firm and of its partner on the firm’s *cash ETR3* [$t_1; t_3$]:

$$\begin{aligned}
cash\ ETR3_{i,t=1} = & \beta_0 + \beta_1 Own_ind_adj_pre_cash_ETR3_{i,t=0} \\
& + \beta_2 Partner_ind_adj_pre_cash_ETR3_{i,t=0} \\
& + \sum_n \beta_n partner\ controls_{i,t=1}^n \\
& + \sum_l \beta_l network\ controls_{i,t=1}^l \\
& + \sum_k \beta_k firm\ controls_{i,t=1}^k + \varepsilon_{i,t}.
\end{aligned} \tag{7}$$

Since we use industry-adjusted measures of *cash ETR3* in this model, we do not insert industry fixed effects. However, we include the indicator *SameInd* in addition to the *partner controls* (*SameAuditor*, *Proximity*). If the partner firm’s tax position were correlated with the firm’s own levels of tax planning, one would find a positive coefficient estimate of *Partner_ind_adj_pre_cash_ETR3*. In a first specification of equation (7), we include network-firm-observations of low-tax firms and high-tax firms. The results are depicted in Panel A of Table 7. While we observe a positive and highly significant coefficient estimate of *Own_ind_adj_pre_cash_ETR3*, *Partner_ind_adj_pre_cash_ETR3* is not significant. The latter finding is, however, little surprising

given the inference that low-tax firms are rather unaffected by their partner firms' tax positions (Table 6 Panel C). Therefore, we include network-firm-observations of high-tax firms in a second specification of equation (7). In this model, the coefficient estimate of *Partner_ind_adj_pre_cash_ETR3* is significant (p-value 0.0936). Consistent with the findings from our main analysis and with the notion of tax knowledge diffusion via strategic alliances, we find a positive association between partner firms' cash effective tax rates.

8. Conclusion

The purpose of this study is to further shed light on channels through which tax knowledge diffuses between firms. Despite solid insights on within-firm determinants of corporate tax planning, research on cross-firm connections in this field is still developing. We contribute to this emerging literature by being the first to identify strategic alliances as channels of tax knowledge diffusion between firms. Using data on strategic alliances between publicly traded US firms, we are able to distinguish between networks that bring together high-tax and low-tax firms and networks that are established among high-tax firms respectively. Our results suggest that strategic alliances provide channels through which tax knowledge diffuses from low-tax firms to undersheltered firms. This identified channel should interest corporate executives, regulators, and researchers because the perception and valuation of the documented spillovers highly depend on the respective point of view.

Although prior research has dedicated substantial attention to corporate cooperation and individual firms' tax planning, there are a number of unanswered questions regarding the interplay of the two. Primarily, we encourage research on the actual mechanisms of tax knowledge diffusion. Furthermore, it remains unclear whether the tax position of a potential network partner influences the decision of a firm to invest in a specific strategic alliance. Our hope is that our study enhances interdisciplinary research in accounting and management.

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Appendix: Variable Definitions

Variable	Definition (Compustat/SDC equivalent)
Network Characteristics	
<i>high-tax network</i>	Equals 1 for networks with solely high-tax firms as participants.
<i>hightolow</i>	Indicator variable; equals 1 for high-tax firms in low-tax networks; equals 0 for high-tax firms in high-tax networks; if a firm enters into multiple networks in one year, only one observation of this firm enters our sample in this year. In these cases, network selection is primarily done on a randomized basis. However, if a firm entered as high-tax firm into a low-tax network and into (a) high-tax network(s) in one year, we keep the low-tax network observation.
<i>low-tax network</i>	Equals 1 for networks involving at least one low-tax firm.
<i>lowtohigh</i>	Indicator variable; equals 1 for low-tax firms in high-tax networks; equals 0 for low-tax firms in low-tax networks.
\sum <i>network controls</i>	Indicator variables for the main business purpose of a network, which is derived from a network's deal description (DealText) in SDC; comprises PurposeWholesale, PurposeRnD, PurposeLicensing, PurposeService, PurposeMarketing, PurposeSupply and PurposeManufacture; information is systematically extracted with R: dofile available upon request.
Partner Characteristics	
<i>Proximity</i>	Distance (as the crow flies) between the participants of a network according to the zip code of the participants' headquarters (addzip); collected from freemaptools.com; normalized between 1 and 0 for closest (same addzip) and farthest distance.
<i>SameAuditor</i>	Indicator variable; equals 1 when all participants of a network share the same auditor firm (au) in the year of network initiation; 0 otherwise; by nature of construction missing for non-network-firm-observations.
<i>SameInd</i>	Constructed as SameAuditor but for industry affiliation; industry is classified using two-digit SIC codes (sic); see also Table 2.
<i>SameBEARegion</i>	Constructed as SameAuditor; equals 1 when all network participants are located in the same BEA region in the year of network initiation; 0 otherwise; the respective regions, as defined by the Bureau of Economic Analysis, are Far West, Great Lakes, Mideast, New England, Plains, Rocky Mountains, Southeast and Southwest.
\sum <i>partner controls</i>	See Proximity and SameAuditor for main analysis (equation (3)).

Variable	Definition (Compustat/SDC equivalent)
Firm Characteristics	
<i>cash ETR</i>	Cash effective tax rate; defined as cash taxes paid (txpd) divided by pre-tax income (pi) before special items (spi); special items are reset to 0 when missing; cash ETR observations with negative denominator are reset to missing; winsorized at 0 and 1.
<i>cash ETR3</i>	Cash effective tax rate; defined as cash taxes paid (txpd) divided by pre-tax income (pi) before special items (spi); special items are reset to 0 when missing; numerator and denominator are constructed as the sum of the current and two subsequent years; observations with negative denominator are reset to missing; for the final (penultimate) firm-year of a firm substituted by cash ETR(2); winsorized at 0 and 1.
<i>cash ETR5</i>	Cash effective tax rate; constructed as cash ETR3, but for five years.
<i>ChangeEBITDA3</i>	Three-year annual average growth rate (geometric mean) of EBITDA (ebitda) ($\sqrt[3]{ebitda_{t3}/ebitda_{t1}} - 1$); reset to 0 when missing.
<i>ChangePIF03</i>	Constructed as ChangeEBITDA3, but for foreign pre-tax income (pifo).
<i>ChangeNOL3</i>	Constructed as ChangeEBITDA3, but for tax loss carry forward (tlcf).
<i>delta cash ETR3</i>	Cash ETR3 [t ₁ ; t ₃] scaled by pre cash ETR3 [t ₂ ; t ₀].
<i>delta cash ETR5</i>	Cash ETR5 [t ₁ ; t ₅] scaled by pre cash ETR3 [t ₂ ; t ₀].
<i>high-tax firm</i>	Indicator variable; equals 1 when a firm's industry adjusted pre cash ETR3[t ₂ ; t ₀] is aligned to pre taxrank [2; 4] (if pre taxrank[t ₀] is missing, replaced by pre taxrank[t ₁]); 0 otherwise.
<i>low-tax firm</i>	Indicator variable; equals 1 when a firm's industry adjusted pre cash ETR3[t ₂ ; t ₀] is aligned to pre taxrank = 1 (if pre taxrank[t ₀] is missing, replaced by pre taxrank[t ₁]); 0 otherwise.
<i>post</i>	Indicator variable; equals 0 for a period of three years before network initiation and 1 for a period of five years subsequent to initiation and includes treatment/control observations. post constitutes an embargo period during which no other hightolow observation may occur.
<i>pre cash ETR3</i>	Constructed as cash ETR3 but with numerator and denominator constructed as the sum of the current and two preceding periods; for first (second) firm-year of a firm substituted by pre cash ETR(2).
<i>pre taxrank</i>	Allocates ranks (1-4) according to the quartiles of the distribution of industry adjusted pre cash ETR3; 1 for the bottom end, 4 for the top end of the distribution.
<i>treated</i>	Treatment is in alignment with hightolow (see post for embargo period) and extended to pre- and post-periods.
<i>treated * post</i>	Interaction of treated and post; main variable of interest in difference-in-differences model.

Variable	Definition (Compustat/SDC equivalent)
Firm Controls*	
<i>AdExp3</i>	Advertising expense (xad) divided by net sales (sale); numerator and denominator are constructed as the sum of the current and two subsequent years; when missing reset to annual measure, thereafter reset to 0.
<i>CapEx3</i>	Reported capital expenditures (capx) divided by gross property, plant, and equipment (ppeg); numerator and denominator are constructed as the sum of the current and two subsequent years; when missing reset to annual measure, thereafter reset to 0.
<i>Cash3</i>	Cash and cash equivalents (che) divided by total assets (at); numerator and denominator are constructed as the sum of the current and two subsequent years; when missing reset to annual measure, thereafter reset to 0.
<i>ChangeSale3</i>	Three-year annual average growth rate (geometric mean) of net sales (sale) ($\sqrt[3]{sale_{t3}/sale_{t1}} - 1$); when missing reset to annual change, thereafter reset to 0.
<i>EBITDA3</i>	Earnings before interest, taxes, depreciation and amortization (ebitda) scaled by total assets (at); numerator and denominator are constructed as the sum of the current and two subsequent years; when missing reset to annual measure, thereafter reset to 0.
<i>Intangibles3</i>	The ratio of intangible assets (intan) to total assets (at); numerator and denominator are constructed as the sum of the current and two subsequent years; when missing reset to annual measure, thereafter reset to 0.
<i>Leverage3</i>	The sum of long-term debt (dltt) and long-term debt in current liabilities (dlc) divided by total assets (at); numerator and denominator are constructed as the sum of the current and two subsequent years; when missing reset to annual measure, thereafter reset to 0.
<i>MNE3</i>	Indicator variable; equals 1 if pifo > 0 (non-missing, non-zero value for pre-tax income from foreign operations), 0 otherwise; measured as the sum over three years.
<i>NOL3</i>	Indicator variable equals 1 if tlcf > 0 (non-missing, non-zero value of tax loss carry forward), 0 otherwise; measured as the sum over three years.
<i>PPE3</i>	Gross property, plant, and equipment (ppeg) divided by total assets (at); numerator and denominator are constructed as the sum of the current and two subsequent years; when missing reset to annual measure, thereafter reset to 0.
<i>RnDExp3</i>	Research and development expenses (xrd) scaled by net sales (sale); numerator and denominator are constructed as the sum of the current and two subsequent years; when missing reset to annual measure, thereafter reset to 0.

Variable	Definition (Compustat/SDC equivalent)
<i>SGA3</i>	Selling, general, and administrative expense (xsga); divided by net sales (sale); numerator and denominator are constructed as the sum of the current and two subsequent years; when missing reset to annual measure, thereafter reset to 0.
<i>Size3</i>	The natural log of total assets (at) for the respective and two subsequent periods; when missing reset to annual measure, thereafter reset to 0.

*Continuous *firm controls* are winsorized at p1 and p99 and not mean centered.

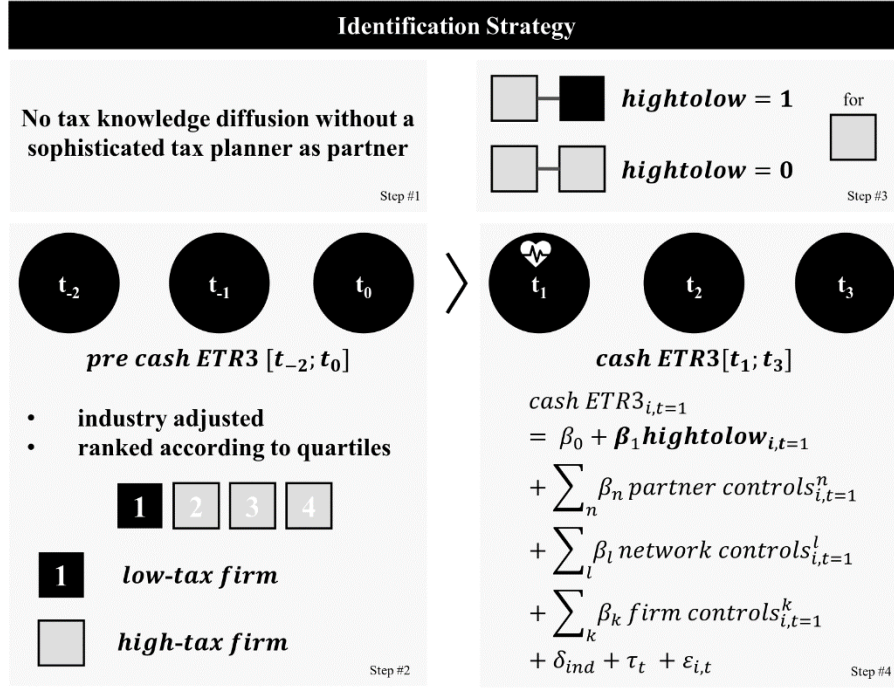
Figures

Figure 1

Literature on Tax Knowledge Diffusion		
Framework	1 Intermediary	2 Peer-to-Peer
Major Channel	A Explicit Transfer	B Spillover
1 — A	<ul style="list-style-type: none"> • Auditors (Frey (2018); Lim et al. (2018)) • Banks (Gallemore, Gipper, Maydew (2018)) • Board Ties (Brown (2011); Brown, Drake (2014)) • Human Capital Turnover (Barrios, Gallemore (2018)) 	
2 — A	<ul style="list-style-type: none"> • Supply Chains (Cen et al. (2017); Cen et al. (2018)) 	
2 — B	<ul style="list-style-type: none"> • Strategic Alliances 	

This figure categorizes prior research regarding tax knowledge diffusion. It aligns the framework (institutional setting) of the identified channels.

Figure 2



This figure summarizes our identification strategy. For simplification purposes, we show the strategic alliances of two participants in the upper right corner. The heartbeat pictogram at t_1 indicates the year of initiation of a strategic alliance. We also show a specification of equation (3), where *Tax Knowledge* is measured as *cash ETR3*.

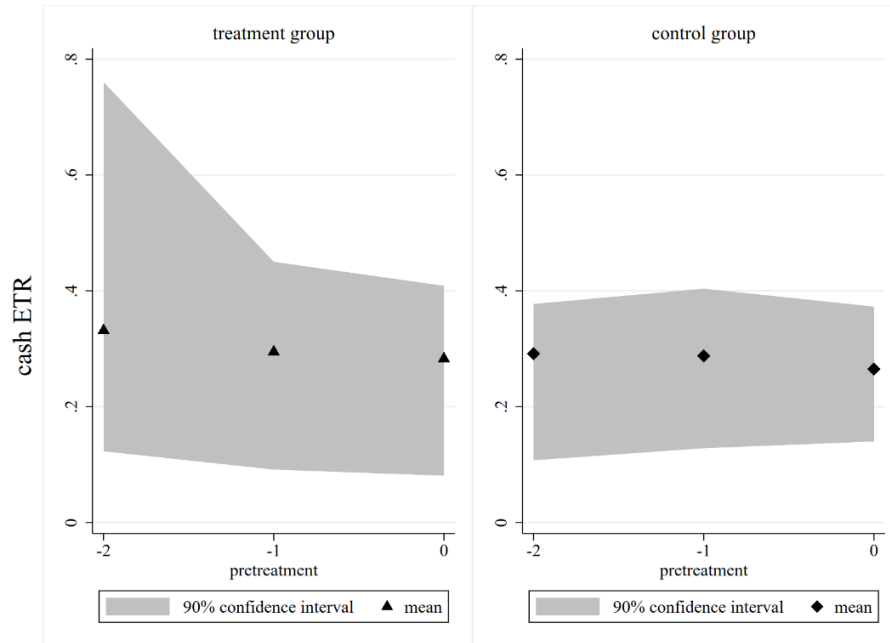
Figure 3



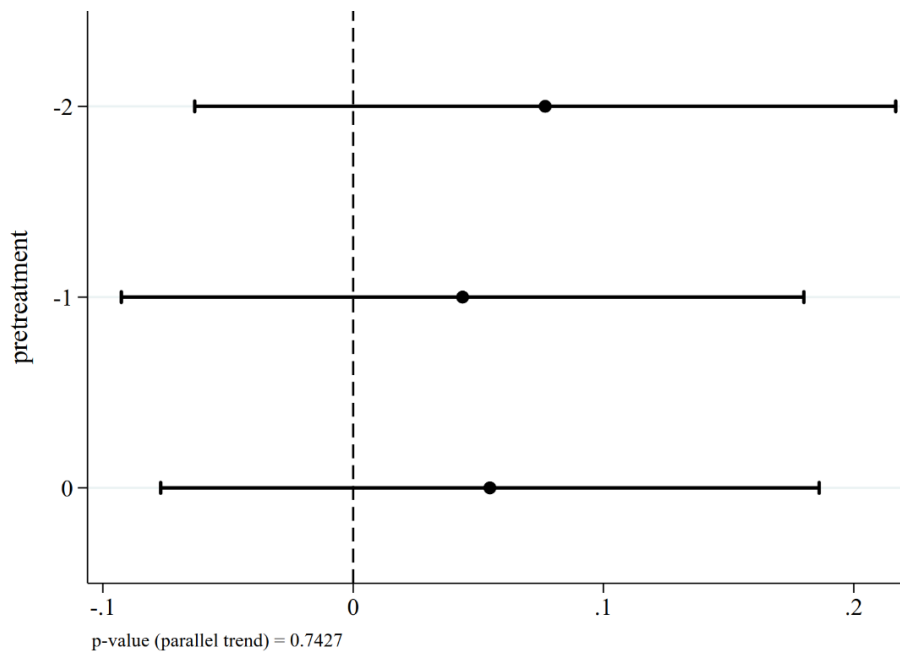
The word cloud depicted in Figure 3 shows the 50 most common words used in SDC's deal description of *hightolow* networks. By systematically searching through the deal descriptions, we identify *wholesale*, *licensing*, *marketing* and *manufacturing* activities as well as *research and development*, providing *services* and engaging in a *supply chain* as major business purposes of the networks in our sample.

Figure 4

Panel A

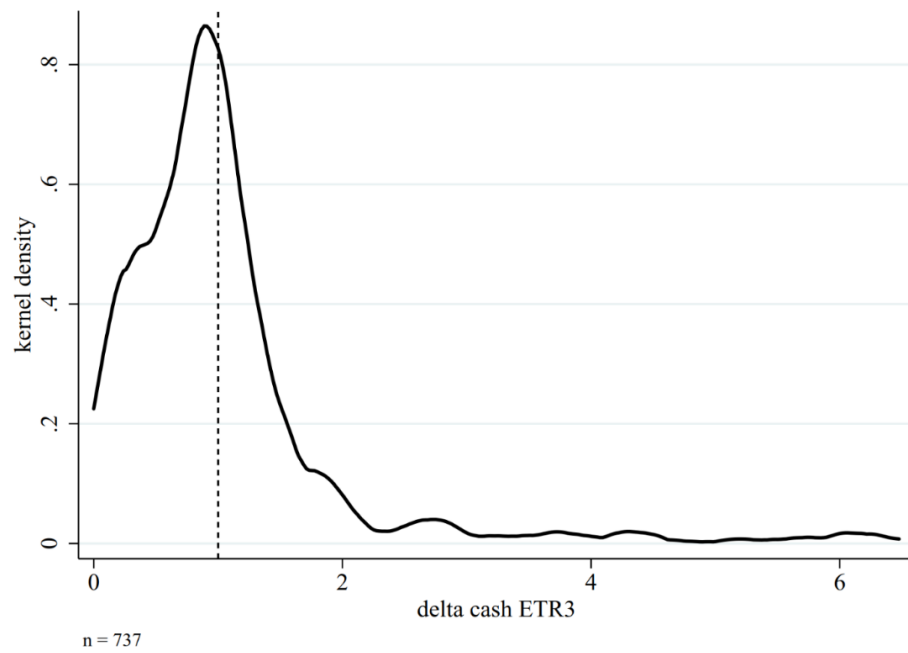


Panel B



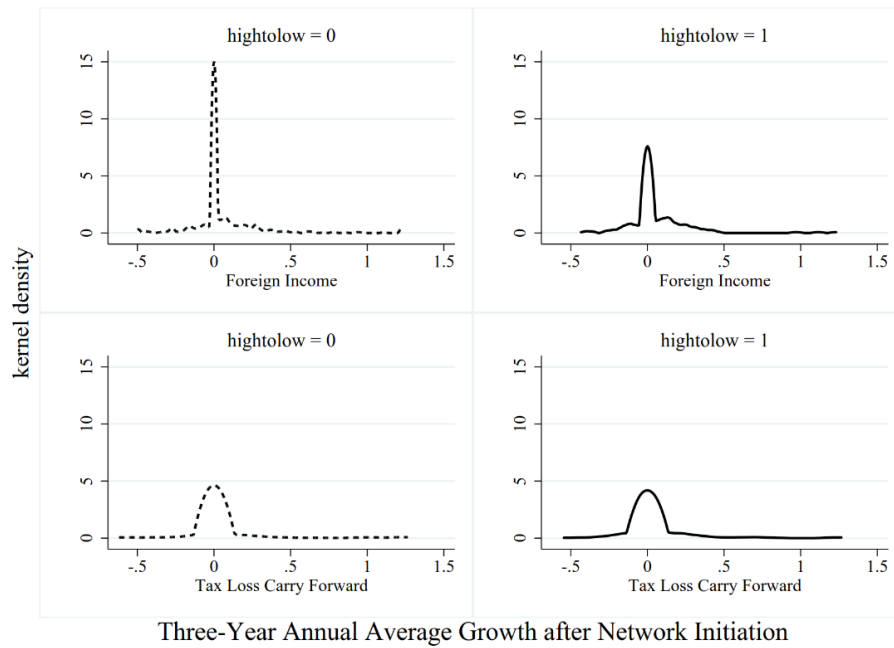
Panel A of this figure provides visual evidence that the trend of cash ETR is similar for treatment and control firms prior to the treatment. In Panel B, we apply the approach by Patel and Seegert (2015) to provide statistical evidence for the parallel trend assumption. The panel reports the coefficient and 95% confidence interval of the interaction of the treatment indicator and time fixed effects for pretreatment years from the specification $cash\ ETR_{i,t} = \beta_0 + \beta_1 * treated_i + \tau_t + \tau_t * treated_i + \varepsilon_{i,t}$. We test that the coefficients on $\tau_t * treated_i$ are jointly zero in the pretreatment period and fail to reject the null hypothesis. This supports the parallel trend assumption. The p-value for the parallel trend test is reported at the bottom of Panel B.

Figure 5



This figure depicts a kernel density plot of the distribution of *delta cash ETR3* for high-tax firms. The dotted line at $x = 1$ indicates the threshold between a decrease and an increase in *cash ETR3* relative to *pre cash ETR3*. The Appendix contains detailed definitions of all variables.

Figure 6



This figure depicts the kernel density distribution of the three-year annual average growth in foreign pretax income (*pifo*) and tax loss carry forward (*tlcf*) for high-tax firms in high-tax and low-tax networks (*hightolow* = 1 vs. 0).

Tables

Table 1 Sample Selection & Identification Strategy

Panel A Compustat & SDC Platinum Data

	network-firm-observations	networks	firms	firm-years
Compustat and SDC Platinum dataset of network firms matched according to year of network initiation (DateEffective), US firms only (loc, fic, curcd), sample period 1994 - 2016 (fyear)	17798	15387	3570	52914
./ requirement to identify all contracting parties in network	4159	2064	1603	19447

Panel B Identification Strategy: Missing Information

	network-firm-observations
all network-firm-observations in sample	4159
./ missing pre cash ETR3 [t-2; t0]	2520
./ missing cash ETR3 [t1; t3]	2247
./ requirement to identify pre cash ETR3 and cash ETR3 of all participants in network	1301

Panel C Identification Strategy: Classification of network-firm-observations

	low-tax partner	high-tax partner	Σ
low-tax firm [including multiple new networks of a firm in one year]	58 [78]	159 [225]	217 [303]
high-tax firm [including multiple new networks of a firm in one year]	197 [226]	540 [772]	737 [998]
	255 [304]	699 [997]	954 [1301]

All variables are defined in detail in the Appendix. Data items from Compustat and SDC Platinum are in parentheses.

Table 2 Information on Networks and Firms**Panel A pre cash ETR3 by pre taxrank**

	N	mean	min	p5	p25	p50	p75	p95	max
pre taxrank = 1	2872	0.0708	0.0000	0.0000	0.0228	0.0699	0.1136	0.1515	0.2213
pre taxrank = 2	2872	0.2104	0.1055	0.1549	0.1836	0.2107	0.2367	0.2643	0.3255
pre taxrank = 3	2872	0.3062	0.2161	0.2577	0.2801	0.3047	0.3316	0.3602	0.4197
pre taxrank = 4	2872	0.6391	0.3094	0.3559	0.3973	0.4979	1.0000	1.0000	1.0000
pre cash ETR3	11488	0.3066	0.0000	0.0141	0.1527	0.2599	0.3574	1.0000	1.0000

Panel B Descriptive Statistics

	low-tax firm in network			high-tax firm in low-tax network (hightolow = 1)			high-tax firm in high-tax network (hightolow = 0)		
	N	mean	p50	N	mean	p50	N	mean	p50
cash ETR	294	0.1396	0.1166	193	0.2708	0.2533	520	0.2918	0.2659
cash ETR3	303	0.2017	0.1544	197	0.2755	0.2516	540	0.3282	0.2715
cash ETR5	231	0.1836	0.1618	162	0.2366	0.2313	434	0.2697	0.2586
EBITDA3	303	0.1387	0.1291	197	0.1527	0.1455	540	0.1582	0.1503
RnDExp3	303	0.1031	0.0959	197	0.0737	0.0489	540	0.0614	0.0296
AdExp3	303	0.0129	0.0000	197	0.0147	0.0000	540	0.0138	0.0000
SGA3	303	0.3471	0.3363	197	0.2702	0.2720	540	0.2599	0.2432
CapEx3	303	0.2082	0.1488	197	0.1536	0.1131	540	0.1598	0.1258
ChangeSale3	303	0.0693	0.0524	197	0.0484	0.0337	540	0.0605	0.0393
Leverage3	303	0.1681	0.1123	197	0.1815	0.1849	540	0.1942	0.1879
Cash3	303	0.2647	0.2180	197	0.1818	0.1254	540	0.1657	0.1040
MNE3	303	0.6931	1.0000	197	0.6041	1.0000	540	0.5444	1.0000
NOL3	303	0.3432	0.0000	197	0.3503	0.0000	540	0.2722	0.0000
Intangibles3	303	0.1556	0.0854	197	0.1844	0.1363	540	0.1585	0.0877
PPE3	303	0.3067	0.2204	197	0.4116	0.3313	540	0.4341	0.3286
Size3	303	9.1756	9.1257	197	9.6259	9.5942	540	9.1201	9.2695

Table 2 Information on Networks and Firms (continued)

Panel C Industry Affiliation of Networks and Firms (two-digit SIC-code)

	#	industry of networks												Σ
		I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII	
industry of firms	Agriculture, Forestry, & Fishing (01-09)	I	0	0	0	1	0	1	0	0	0	0	0	2
	Mining (10-14)	II	0	6	0	1	2	0	2	0	0	1	0	12
	Construction (15-17)	III	0	0	0	0	0	3	0	0	0	1	0	4
	Manufacturing: Chemical & Allied Products (28)	IV	0	0	0	26	15	0	23	0	20	8	35	127
	Manufacturing (20-39, except 28)	V	0	4	2	11	167	17	41	4	39	131	48	471
	Transportation & Public Utilities (40-49)	VI	0	3	2	0	7	32	4	0	1	30	10	89
	Wholesale Trade (50-51)	VII	0	1	0	0	3	2	19	1	3	8	4	41
	Retail Trade (52-59)	VIII	0	0	0	0	4	3	9	1	4	10	2	35
	Finance, Insurance, & Real Estate (60-67)	IX	0	0	0	1	1	1	2	1	25	17	6	56
	Services: Business Services (73)	X	0	0	0	1	31	10	21	3	22	273	22	386
	Services (70-89, except 73)	XI	0	0	0	0	0	3	2	0	4	8	16	33
	Nonclassifiable Establishments (99)	XII	0	0	0	3	8	6	1	0	4	15	8	45
			0	14	4	44	238	78	124	10	122	500	153	1301

All variables are defined in detail in the Appendix.

Table 3 Descriptive Analysis

Panel A Comparison of cash ETR3 change between and within groups

		high-tax firm in low-tax network (hightolow = 1)		high-tax firm in high-tax network (hightolow = 0)		difference	p-value
		N	mean	N	mean		
pre cash ETR3 [t-2; t0]	I	197	0.3896	540	0.3935	- 0.0039	(0.8613)
cash ETR3 [t1; t3]	II	197	0.2755	540	0.3282	- 0.0527 ***	(0.0065)
Within-group change (hightolow = 1)	I to II					- 0.1141 ***	(0.0000)
Within-group change (hightolow = 0)	I to II					- 0.0653 ***	(0.0000)
Difference in within-group change						- 0.0488 *	-1.6994

Panel B Comparison of cash ETR3-development for intensified networking

		high-tax firm in low-tax network (hightolow = 1)		high-tax firm in high-tax network (hightolow = 0)		difference	p-value
		N	mean	N	mean		
1 st and 2 nd high-/low-tax network	I	153	0.2922	418	0.3390	- 0.0468 **	(0.0376)
subsequent (≥ 3) high-/low-tax networks	II	44	0.2174	122	0.2915	- 0.0740 **	(0.0455)

All variables are defined in detail in the Appendix.

Table 4 Main Analysis

Panel A Regression Analysis

Dependent variable	cash ETR3		delta cash ETR3		cash ETR5		delta cash ETR5	
	coefficient	p-value	coefficient	p-value	coefficient	p-value	coefficient	p-value
hightolow	- 0.0480**	(0.0103)	- 0.2062***	(0.0061)	- 0.0376***	(0.0087)	- 0.1229**	(0.0191)
Proximity	- 0.0877	(0.1171)	- 0.2488	(0.2795)	0.0269	(0.4762)	0.1089	(0.4028)
SameAuditor	- 0.0107	(0.6173)	- 0.0427	(0.6201)	0.0107	(0.5414)	0.0309	(0.6342)
Network controls	Yes		Yes		Yes		Yes	
Firm controls	Yes		Yes		Yes		Yes	
Fixed effects	Industry & Year		Industry & Year		Industry & Year		Industry & Year	
SE cluster	Firm		Firm		Firm		Firm	
Observations	735		735		594		594	
Adjusted R2	0.1233		0.1047		0.0577		0.1228	

Superscripts ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively, for two-tailed tests. The results for equation (3) are presented in Panel A. Our main variable of interest is *hightolow*, which is an indicator variable set equal to 1 for observations of high-tax firms cooperating with low-tax firms and set equal to 0 for high-tax firms cooperating with high-tax firms. The number of observations is decreased from 737 to 735 (596 to 594) by two singleton observations in the fixed effects. All variables are defined in detail in the Appendix.

Table 4 Main Analysis (continued)

Panel B Matched Panel: Difference-in-Differences

Dependent variable	cash ETR		cash ETR		cash ETR	
	coefficient	p-value	coefficient	p-value	coefficient	p-value
treated	0.0221	(0.3097)	0.0140	(0.5047)	0.0137	(0.5268)
post	0.0364 **	(0.0372)	0.0374 **	(0.0291)	0.0350 *	(0.0536)
treated*post	- 0.0695 **	(0.0159)	- 0.0710 **	(0.0132)	- 0.0699 **	(0.0131)
Firm controls	No		No		Yes (annual measures)	
Fixed effects	No		Industry		Industry	
SE cluster	Firm		Firm		Firm	
Observations	609		609		609	
Adjusted R2	0.0052		0.0239		0.0431	

Superscripts ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively, for two-tailed tests. Panel B depicts the results for equation (4). We compose our sample by creating an embargo period of eight years (from -3 to +5 years) around an *hightolow* observation during which no further *hightolow* observations may occur. We match control observations (*hightolow* = 0) according to year and industry to each treatment occurrence (*hightolow* = 1). All variables are defined in detail in the Appendix.

Table 4 Main Analysis (continued)

Panel C Adjustment Speed		
Dependent variable	cash ETR	
(#) of specification	coefficient	p-value
(1) treated*post [t1]	- 0.0555	(0.1946)
(2) treated*post [t1; t2]	- 0.0988 **	(0.0154)
(3) treated*post [t1; t3]	- 0.0697 **	(0.0423)
(4) treated*post [t1; t4]	- 0.0765 **	(0.0118)
(5) treated*post [t1; t5]	- 0.0699 **	(0.0131)
Controls	Firm (annual measures) & treated & post	
Fixed effects	Industry	
SE cluster	Firm	
Observations	331; 405; 479; 545; 609	
Adjusted R2	0.0403; 0.0505; 0.0359; 0.0420; 0.0431	

Superscripts ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively, for two-tailed tests. Panel C depicts the results for five specifications of equation (4). The posttreatment period is extended by one year for each specification (from $post = 1$ for $[t_1]$ to $post = 1$ for $[t_1; t_5]$). $post$ remains 0 for t_{-2} to t_0 throughout all specifications. The coefficient estimates for $treatment * post$ present the cumulative adjustment (i.e. adjustment speed) in a high-tax firm's tax planning behavior with progressing time when cooperating with low-tax firms.

Table 5 Additional Analyses

Panel A Headquarters

Dependent variable	cash ETR3		delta cash ETR3	
	coefficient	p-value	coefficient	p-value
hightolow	- 0.0579 ***	(0.0033)	- 0.1912 **	(0.0107)
SameBEARegion	- 0.0316	(0.1938)	- 0.0474	(0.6590)
hightolow*SameBEARegion	0.0524	(0.2386)	- 0.0486	(0.7772)
Controls	Network & Firm		Network & Firm	
Fixed effects	Industry & Year		Industry & Year	
SE cluster	Firm		Firm	
Observations	735		735	
Adjusted R2	0.1233		0.1040	

Panel B Industry

Dependent variable	cash ETR3		delta cash ETR3	
	coefficient	p-value	coefficient	p-value
hightolow	- 0.0678 ***	(0.0078)	- 0.2505 **	(0.0197)
SameInd	- 0.0403 *	(0.0530)	- 0.1567 *	(0.0735)
hightolow*SameInd	0.0526	(0.1267)	0.1348	(0.3235)
Controls	Network & Firm		Network & Firm	
Fixed effects	Year		Year	
SE cluster	Firm		Firm	
Observations	736		736	
Adjusted R2	0.1215		0.1079	

Table 5 Additional Analyses (continued)

Panel C Auditor				
Dependent variable	cash ETR3		delta cash ETR3	
	coefficient	p-value	coefficient	p-value
hightolow	- 0.0428 **	(0.0367)	- 0.2152 ***	(0.0077)
SameAuditor	- 0.0042	(0.8833)	0.0594	(0.5950)
hightolow*SameAuditor	- 0.0237	(0.5566)	0.0642	(0.6976)
Controls	Network & Firm		Network & Firm	
Fixed effects	Industry & Year		Industry & Year	
SE cluster	Firm		Firm	
Observations	735		735	
Adjusted R2	0.1213		0.1037	

Superscripts ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively, for two-tailed tests. In Panel A, we test for the impact of geographical distance between the headquarters of cooperating firms. Distance is measured by an indicator variable that is set equal to one if network participants are headquartered in the same region, as defined by the Bureau of Economic Analysis, at network initiation. Panel B follows the approach of Panel A for the industry affiliation of network participants. We interact *hightolow* with an indicator for changes to a shared audit firm within three years of the network initiation in Panel C. All variables are defined in detail in the Appendix.

Table 6 Robustness Checks: Alternative Explanations

Panel A Survivorship Bias

Dependent variable	cash ETR3	
Specification	exclude nonsurvivors	
	coefficient	p-value
hightolow	- 0.0279*	(0.0571)
Proximity	- 0.0663	(0.1718)
SameAuditor	- 0.0109	(0.5264)
Network controls	No	
Firm controls	Yes	
Fixed effects	Industry & Year	
SE cluster	Firm	
Observations	638	
Adjusted R2	0.0966	

Panel B Increases in cash ETR3

Dependent variable	delta cash ETR3	
Specification	only if delta cash ETR ≤ 1	
	coefficient	p-value
hightolow	- 0.0543*	(0.0950)
Proximity	- 0.0398	(0.7199)
SameAuditor	- 0.0216	(0.5289)
Network controls	No	
Firm controls	Yes	
Fixed effects	Industry & Year	
SE cluster	Firm	
Observations	455	
Adjusted R2	0.1603	

Panel C Impact on low-tax firms

Dependent variable	cash ETR3	
Specification	only low-tax firms	
	coefficient	p-value
lowtohigh	- 0.0002	(0.9961)
Proximity	0.2021	(0.1885)
SameAuditor	- 0.0140	(0.5520)
Network controls	No	
Firm controls	Yes	
Fixed effects	Industry & Year	
SE cluster	Firm	
Observations	301	
Adjusted R2	0.0666	

Panel D Effect on Profitability

Dependent variable	ChangeEBITDA3	
	coefficient	p-value
hightolow	- 0.0069	(0.6569)
Proximity	0.0287	(0.4767)
SameAuditor	- 0.0194	(0.1936)
Network controls	Yes	
Firm controls	Yes (no EBITDA3)	
Fixed effects	Industry & Year	
SE cluster	Firm	
Observations	735	
Adjusted R2	0.3577	

Superscripts ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively, for two-tailed tests. In Panel A, nonsurvivors are excluded from the sample. A firm is deemed a nonsurvivor if the year of network initiation is the final or penultimate fiscal year of coverage of this firm in our panel. Panel B excludes increases in *cash ETR3* [$t_1; t_3$] in comparison to *pre cash ETR3* [$t_{-2}; t_0$]. We change our focus from high-tax to low-tax firms in Panel C and construct an indicator variable *lowtohigh*, which is set equal to one for low-tax firms in networks with high-tax firms and equal to zero for low-tax firms in networks with other low-tax firms. We cannot include *network controls* because we have the relevant information for networks of high-tax firms. In Panel D, we control for the (three-year) average annual growth rate in EBITDA (*ChangeEBITDA3*) subsequent to network initiation. All variables are defined in detail in the Appendix.

Table 7 Robustness Checks: Identification Strategy

Panel A Low-tax- and high-tax firms			Panel B Only high-tax firms		
Dependent variable	cash ETR3 [t1; t3]		Dependent variable	cash ETR3 [t1; t3]	
Specification	low-tax- and high-tax firms		Specification	high-tax firms only	
	coefficient	p-value		coefficient	p-value
Own industry-adjusted pre cash ETR3 [t-2; t0]	0.1606***	(0.0000)	Own industry-adjusted pre cash ETR3 [t-2; t0]	0.0616	(0.1216)
Partner industry-adjusted pre cash ETR3 [t-2; t0]	0.0300	(0.2828)	Partner industry-adjusted pre cash ETR3 [t-2; t0]	0.0592*	(0.0936)
Proximity	- 0.0579	(0.1812)	Proximity	- 0.0760	(0.1004)
SameAuditor	- 0.0133	(0.3777)	SameAuditor	- 0.0134	(0.5110)
SameInd	- 0.0249*	(0.0600)	SameInd	- 0.0337*	(0.0551)
Network controls	No		Network controls	Yes	
Firm controls	Yes		Firm controls	Yes	
Fixed effects	No		Fixed effects	No	
SE cluster	Firm		SE cluster	Firm	
Observations	1276		Observations	728	
Adjusted R2	0.1487		Adjusted R2	0.1211	

Superscripts ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively, for two-tailed tests. We examine correlations of cash effective tax rates between network participants. Panel A contains low-tax and high-tax firms in network-firm-observations. Panel B is limited to only high-tax firms. Both panels are limited to networks of two participants. We cannot include *network controls* in Panel A because we collected information for networks of high-tax firms. All variables are defined in detail in the Appendix.

Online Appendix: Information on Networks and Firms

Random Sample of Networks and their main Business Purpose

date effective	high-tax firm name (comm)	partner firm name (comm)	hightolow	deal description [extract]
17-May-95	NOVELL INC	MICROSOFT CORP	1	jointly provide customer service and support expertise in order to meet the needs of customers who use products from both companies
06-Jun-95	3COM CORP	DSP GROUP INC	1	license to use speech compression technology for product (faxmodem)
29-Jan-96	MCI COMMUNICATIONS	MICROSOFT CORP	0	jointly develop and market web services
11-Jun-97	SCHERING-PLOUGH	DENDRITE INTERNATIONAL INC	0	license to provide database software services
26-Sep-97	LOCKHEED MARTIN CORP	CSP INC	0	develop a processor
02-Feb-98	PHARMACIA & UPJOHN INC	CHIRON CORP	0	research Hepatitis C virus and sharing of worldwide marketing rights
11-Jun-98	CARPENTER TECHNOLOGY CORP	ROHM AND HAAS CO	0	license for usage of injection molding technology
06-Jul-98	ELECTRONIC DATA SYSTEMS CORP	ENGINEERING ANIMATION INC	0	cross-license and joint marketing and integration of applications to create interface between visproducts and data management software
01-Dec-98	ACTION PERFORMANCE COS INC	CHAMPSHIP AUTO RACING TEAM	1	manufacture products (cart series and Fedex championship logos) in the United States
06-Jan-99	APPLIED MATERIALS INC	PLASMA-THEMR INC	0	license to cross-integrate product (cluster tool)
19-May-99	SPARTAN MOTORS INC	FEDERAL SIGNAL CORP	0	purchase agreement to improve cost lines and benefit operating units
23-Apr-01	CLOROX CO/DE	OIL DRI CORP AMERICA	0	wholesale and supply of products (cat litter)
21-Aug-02	PEOPLESOFT INC	MERCURY INTERACTIVE CORP	1	accelerate implementation and upgrades of applications for customers
12-Sep-03	BAXTER INTERNATIONAL INC	CURATIVE HEALTH SERVICES INC	1	wholesale of products (drugs for the prevention and control of bleeding)
22-Dec-03	JOHNSON & JOHNSON	ANIKA THERAPEUTICS INC	1	wholesale of products (drugs) with partial prepayment from Johnson & Johnson
22-Jan-07	LOCKHEED MARTIN CORP	BOEING CO	1	marketing and promotional services (air transportation system and equipment)
22-May-07	PACER INTERNATIONAL INC	TRAILER BRIDGE INC	1	provide freight services (container hauling) between United States and Puerto Rico
22-Sep-08	JOHNSON & JOHNSON	ANIKA THERAPEUTICS INC	1	wholesale and distribution of products (drugs for the treatment of pain) in South America, Central America, the Caribbean and Mexico
18-Mar-09	HARRIS CORP	MCAFEES INC	0	develop software (cyber mission management and security software) to provide network operators with heightened levels of situational awareness
12-Feb-13	PFIZER INC	AGILENT TECHNOLOGIES INC	1	develop and commercialize companion diagnostics and provide advisory services

This table provides information regarding the main business purpose of networks (random draw), which are classified either *hightolow* = 1 or *hightolow* = 0.